A long journey into reproducible computational neuroscience research

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A LONG JOURNEY INTO REPRODUCIBLE COMPUTATIONAL NEUROSCIENCE

100% PYTHON !
SPIKE FREE !

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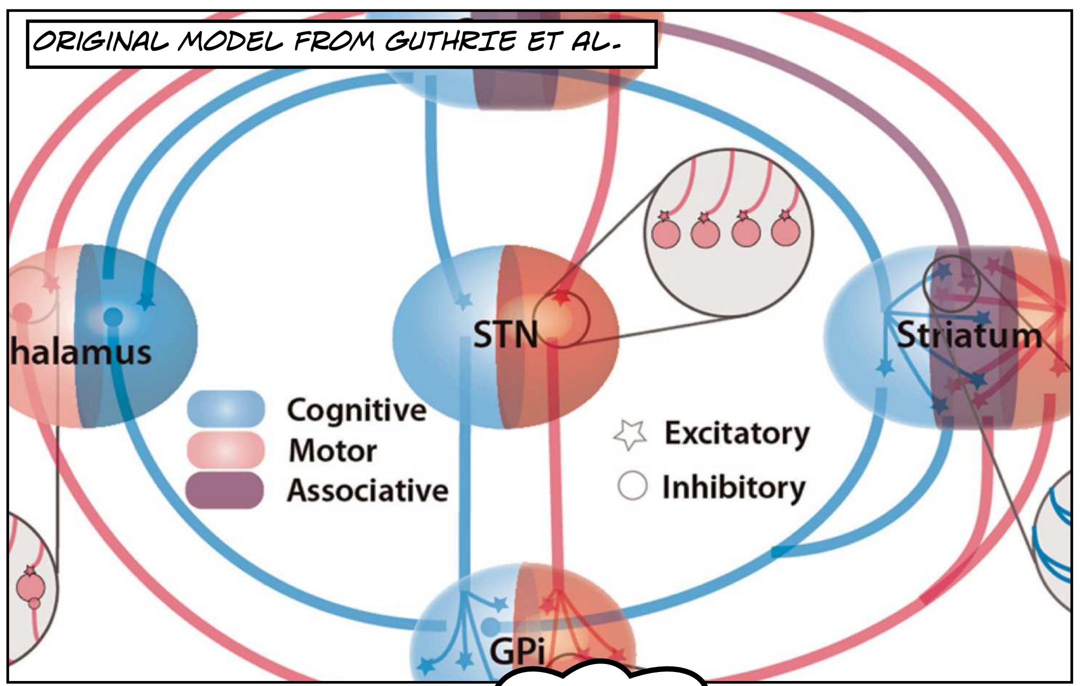
ORIGINAL MODEL FROM GUTHRIE ET AL.



IN A PREVIOUS MODELING STUDY, LEBLOIS ET AL. (2006) DEMONSTRATED AN ACTION SELECTION MECHANISM IN CORTICO-BASAL GANGLIA LOOPS BASED ON COMPETITION BETWEEN THE POSITIVE FEEDBACK, DIRECT PATHWAY THROUGH THE STRIATUM AND THE NEGATIVE FEEDBACK, HYPERDIRECT PATHWAY THROUGH THE SUBTHALAMIC NUCLEUS.

IN GUTHRIE ET AL. (2013), AUTHORS INVESTIGATED HOW MULTIPLE LEVEL ACTION SELECTION COULD BE PERFORMED BY THE BASAL GANGLIA. TO DO THIS, THE MODEL IS EXTENDED IN A MANNER CONSISTENT WITH KNOWN ANATOMY AND ELECTRO-PHYSIOLOGY IN THREE MAIN AREAS. FIRST, TWO-LEVEL DECISION MAKING HAS BEEN INCORPORATED, WITH A COGNITIVE LEVEL SELECTING BASED ON CUE SHAPE AND A MOTOR LEVEL SELECTING BASED ON CUE POSITION. WE SHOW THAT THE DECISION MADE AT THE COGNITIVE LEVEL CAN BE USED TO BIAS THE DECISION AT THE MOTOR LEVEL. WE THEN DEMONSTRATE THAT, FOR ACCURATE TRANSMISSION OF INFORMATION BETWEEN DECISION-MAKING LEVELS, LOW EXCITABILITY OF STRIATAL PROJECTION NEURONS IS NECESSARY, A GENERALLY OBSERVED ELECTROPHYSIOLOGICAL FINDING. SECOND, INSTEAD OF PROVIDING A BIASING SIGNAL BETWEEN CUE CHOICES AS AN EXTERNAL INPUT TO THE NETWORK, WE SHOW THAT THE ACTION SELECTION PROCESS CAN BE DRIVEN BY REASONABLE LEVELS OF NOISE. FINALLY, WE INCORPORATE DOPAMINE MODULATED LEARNING AT CORTICOSTRIATAL SYNAPSES. AS LEARNING PROGRESSES, THE ACTION SELECTION BECOMES BASED ON LEARNED VISUAL CUE VALUES AND IS NOT INTERFERED WITH BY THE NOISE THAT WAS NECESSARY BEFORE LEARNING.

HOWEVER, THE MODEL WAS NOT REPRODUCIBLE FROM THE ARTICLE DESCRIPTION...

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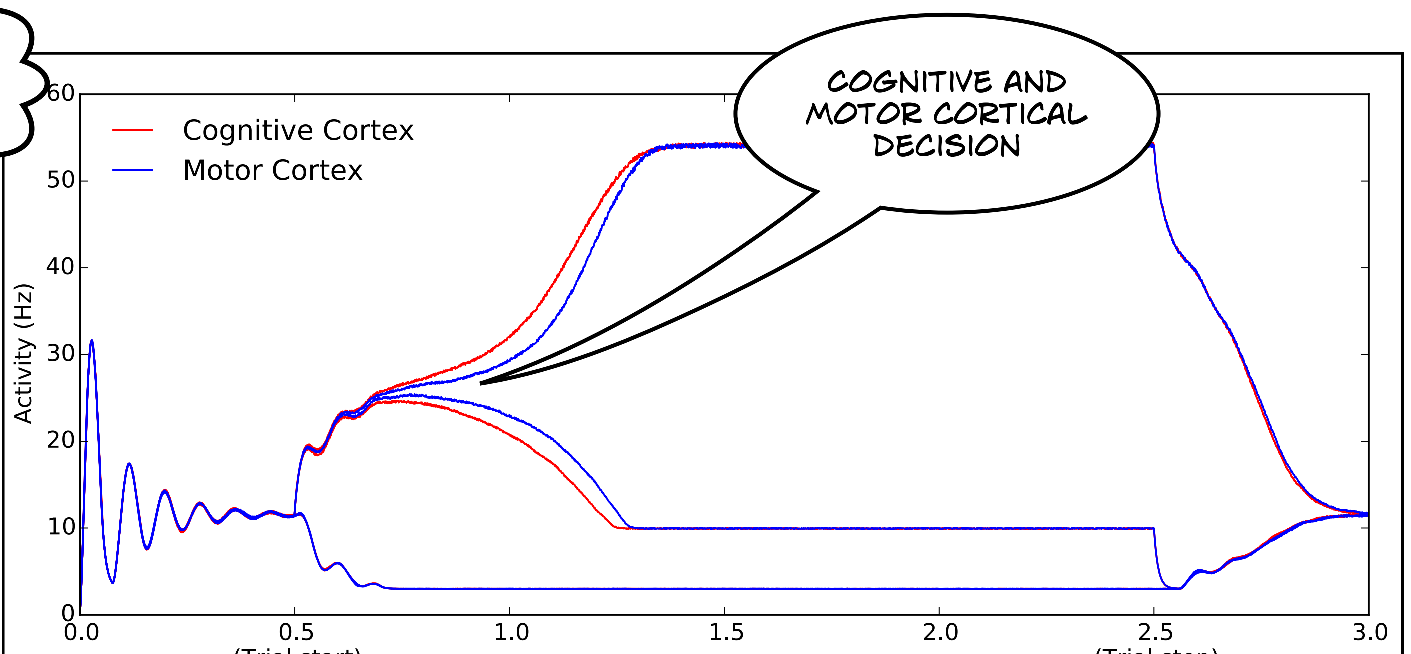
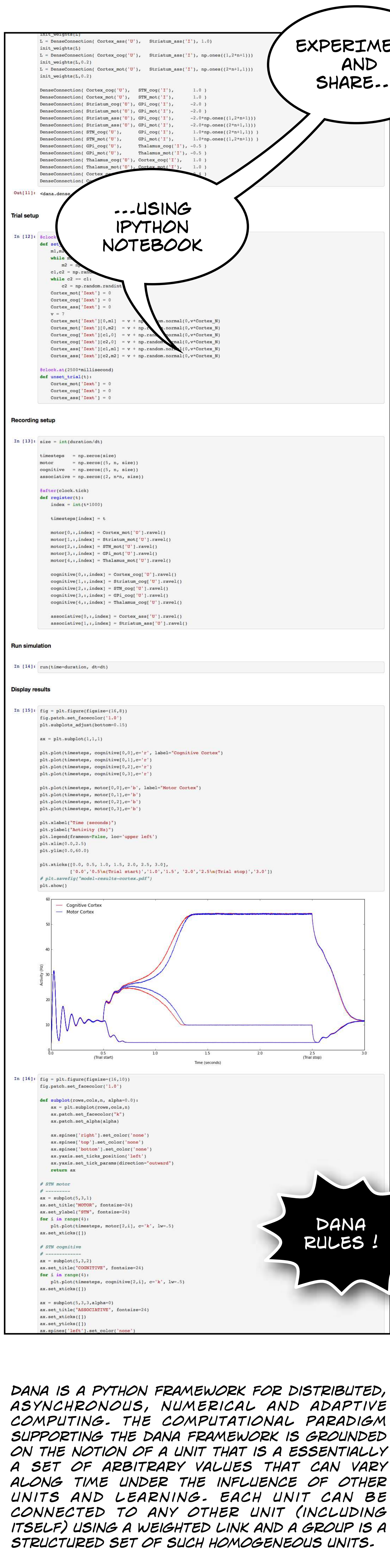


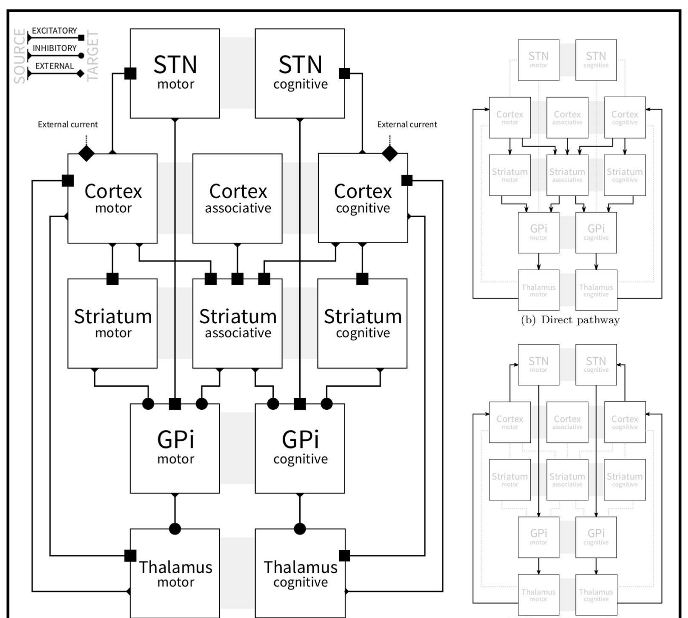
REPRODUCTION OF THE DYNAMIC DECISION SWITCH



IF REPRODUCIBILITY IS THE HALLMARK OF SCIENCE, NON-REPRODUCIBILITY SEEMS TO BE THE HALLMARK OF COMPUTATIONAL NEUROSCIENCES. GUTHRIE ET AL. (2013) IS A PROTOTYPIC CASE OF SUCH NON-REPRODUCIBLE COMPUTATIONAL NEUROSCIENCE RESEARCH EVEN THOUGH THE PROPOSED MODEL GIVES A FAIR ACCOUNT OF DECISION MAKING IN THE BASAL GANGLIA COMPLEX.

WHILE TRYING TO REPLICATE RESULTS STARTING FROM THE ARTICLE DESCRIPTION, WE SOON REALIZED SOME INFORMATION WERE UNDISCLOSED, SOME OTHER WERE AMBIGUOUS AND THERE WERE ALSO SOME FACTUAL ERRORS. EVEN AFTER ACCESSING THE ORIGINAL SOURCES (6000 LINES OF PASCAL), WE WERE STILL UNABLE TO UNDERSTAND HOW THE MODEL WORKED. IN THE END, ONLY THE ORIGINAL MATERIAL (A WINDOWS EXECUTABLE) ALLOWED US TO ACCESS THE MISSING INFORMATION AND AFTER TWO MONTHS OF INTENSIVE REFACTORING, **WE WERE FINALLY ABLE TO REPLICATE RESULTS** USING ONLY 200 LINES OF PYTHON.

UNFORTUNATELY, SUCH LOOSE DESCRIPTION IS NOT AN ISOLATED CASE !!!



CLEAN AND NON AMBIGUOUS FIGURES

TO BE CONTINUED...

BORING BUT INCREDIBLY USEFUL !

A Model Summary	
Populations	Twelve: Cortex (motor, associative & cognitive), Striatum (motor, associative & cognitive), GPi (motor & cognitive), STN (motor & cognitive), Thalamus (motor & cognitive)
Topology	–
Connectivity	one to one, one to many (divergent), many to one (convergent)
Neuron model	Dynamic rate model
Channel model	–
Synapse model	Linear synapse
Plasticity	Reinforcement learning rule
Input	External current in cortical areas (motor, associative & cognitive)
Measurements	Firing rate

B Populations

Name	Elements	Size	Threshold (h)	Noise	Initial state
Cortex motor	Linear neuron	1×4	-3	1.0%	0.0
Cortex cognitive	Linear neuron	4×1	-3	1.0%	0.0
Cortex associative	Linear neuron	4×4	-3	1.0%	0.0
Striatum motor	Sigmoidal neuron	1×4	0	0.1%	0.0
Striatum cognitive	Sigmoidal neuron	4×1	0	0.1%	0.0
Striatum associative	Sigmoidal neuron	4×4	0	0.1%	0.0
GPi motor	Linear neuron	1×4	+10	3.0%	0.0
GPi cognitive	Linear neuron	4×1	+10	3.0%	0.0
STN motor	Linear neuron	1×4	-10	0.1%	0.0
STN cognitive	Linear neuron	4×1	-10	0.1%	0.0
Thalamus motor	Linear neuron	1×4	-40	0.1%	0.0
Thalamus cognitive	Linear neuron	4×1	-40	0.1%	0.0
Values (V_i)	Scalar	4	–	–	0.5

C Connectivity

Source	Target	Pattern	Weight (W)	Gain (G)	Plastic
Cortex motor	Thalamus motor	$(1,i) \to (1,i)$	1.0	0.4	No
Cortex cognitive	Thalamus cognitive	$(i,1) \to (i,1)$	1.0	0.4	No
Cortex motor	STN motor	$(1,i) \to (1,i)$	1.0	1.0	No
Cortex cognitive	STN cognitive	$(i,1) \to (i,1)$	1.0	1.0	No
Cortex motor	Striatum motor	$(1,i) \to (1,i)$	$\mathcal{N}(0.5, 0.005)$	1.0	Yes
Cortex cognitive	Striatum cognitive	$(i,1) \to (i,1)$	$\mathcal{N}(0.5, 0.005)$	1.0	Yes
Cortex motor	Striatum associative	$(1,i) \to (*,i)$	$\mathcal{N}(0.5, 0.005)$	0.2	Yes
Cortex cognitive	Striatum associative	$(i,1) \to (i,*)$	$\mathcal{N}(0.5, 0.005)$	0.2	Yes
Cortex associative	Striatum associative	$(i,j) \to (i,j)$	$\mathcal{N}(0.5, 0.005)$	1.0	Yes
Thalamus motor	Cortex motor	$(1,i) \to (1,i)$	1.0	1.0	No
Thalamus cognitive	Cortex cognitive	$(i,1) \to (i,1)$	1.0	1.0	No
GPi motor	Thalamus motor	$(1,i) \to (1,i)$	1.0	-0.5	No
GPi cognitive	Thalamus cognitive	$(i,1) \to (i,1)$	1.0	-0.5	No
STN motor	GPi motor	$(1,i) \to (1,i)$	1.0	1.0	No
STN cognitive	GPi cognitive	$(i,1) \to (i,1)$	1.0	1.0	No
Striatum cognitive	GPi cognitive	$(i,1) \to (i,1)$	1.0	-2.0	No
Striatum motor	GPi motor	$(i,1) \to (i,1)$	1.0	-2.0	No
Striatum associative	GPi motor	$(*,i) \to (1,i)$	1.0	-2.0	No
Striatum associative	GPi cognitive	$(i,*) \to (i,1)$	1.0	-2.0	No

D1 Neuron Model	
Name	Linear neuron
Type	Rate model
Membrane Potential	$\tau dV/dt = -V + I_{syn} + I_{ext} - h$
	$U = max(V, 0)$

D2 Neuron Model	
Name	Sigmoidal neuron
Type	Rate model
Membrane Potential	$\tau dV/dt = -V + I_{syn} + I_{ext} - h$
	$U = V_{min} - (V_{max} - V_{min}) / \left(1 + e^{\frac{V_h - V}{V_c}}\right)$

E Synapse	
Name	Linear synapse
Type	Weighted sum
Output	$I^B_{syn} = \sum_{A \in sources} (G_{A \to B} W_{A \to B} U_A)$

F Plasticity	
Name	Reinforcement learning
Type	Delta rule
Delta	$\Delta W_{A \to B} = \alpha \times PE \times U_B$
	$PE = Reward - V_i$
	$\alpha = 0.01$ if $PE < 0$ (LTD), $\alpha = 0.02$ if $PE > 0$ (LTP)

G Input	
Type	Cortical input
Description	A trial is preceded by a settling period (500ms) and followed by a reset period. At time $t = 0$, two shapes are presented in cortical cognitive area ($I_{ext} = 7$ at $\{i_1, i_2\}$) at two different locations in cortical motor area ($I_{ext} = 7$ at $\{j_1, j_2\}$) and the cortical associate area is updated accordingly ($I_{ext} = 7$ at $\{i_1, i_2\} \times \{j_1, j_2\}$).
Timing	Trial start -500ms; Stimulus onset 0; Stimulus offset 2500 ms; Reset 3000 ms

H Measurements	
Site	Cortical areas
Data	Activity in cognitive and motor cortex
	Cortico-striatal weights

I Environment	
OS	OSX 10.9 (maverick)
Language	Python 2.7.6 (brew installation)
Libraries	Numpy 1.8.1 (pip installation)
	SciPy 0.13.3 (pip installation)
	IPython 1.2.1 (pip installation)
	Matplotlib 1.3.0 (pip installation)
	DANA 0.5.0 (pip installation)
Tools	Safari browser (native)

TABULAR DESCRIPTION OF THE MODEL FROM NORDLIE ET AL. (2009)

DANA RULES !

DANA IS A PYTHON FRAMEWORK FOR DISTRIBUTED, ASYNCHRONOUS, NUMERICAL AND ADAPTIVE COMPUTING. THE COMPUTATIONAL PARADIGM SUPPORTING THE DANA FRAMEWORK IS GROUNDED ON THE NOTION OF A UNIT THAT IS A ESSENTIALLY A SET OF ARBITRARY VALUES THAT CAN VARY ALONG TIME UNDER THE INFLUENCE OF OTHER UNITS AND LEARNING. EACH UNIT CAN BE CONNECTED TO ANY OTHER UNIT (INCLUDING ITSELF) USING A WEIGHTED LINK AND A GROUP IS A STRUCTURED SET OF SUCH HOMOGENEOUS UNITS.

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